Effects of seasonal climate forecasts and participatory workshops among subsistence farmers in Zimbabwe

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Improvements in the ability to model El Niño and other large-scale interannual climate variations have allowed for the development of seasonal climate forecasts, predicting rainfall and temperature anomalies for many places around the world. These forecasts have allowed developing countries to predict shortfalls in grain yields, with benefits for food security. Several countries communicate the forecasts to subsistence farmers, which could allow them to mitigate the effects of drought on their harvests by adapting their cropping decisions accordingly. However, it has not been demonstrated that subsistence farmers benefit from having access to the forecasts. Here we present evidence of subsistence farmers using the forecasts over multiple years to make different decisions and significantly improving their harvests when they do so. In a controlled study, farmers in Zimbabwe who reported adapting their farming methods to seasonal climate forecasts significantly improved their harvests over baseline amounts. Moreover, farmers who had attended a brief workshop and learned more about the forecasts were significantly more likely to use the forecasts than were farmers who learned of the forecasts through nonparticipatory channels.

climate change | climate forecasting | sustainable development

Among the many effects associated with the El Niño/Southern Oscillation (ENSO) cycle, researchers have identified a correlation between ENSO warm events and dry conditions during the summer growing season in Zimbabwe, where >60% of the variance of maize yields is explained by sea surface temperatures in the eastern equatorial Pacific (1). ENSO forecasts, used to generate national-scale seasonal forecasts of rainfall anomalies, could have economic value to the Zimbabwean agricultural sector if farmers have the opportunity to adapt to expected climatic conditions by planting different crop varieties and changing other management decisions in response to the information (2). Here we show that subsistence farmers in Zimbabwe have used and benefited from seasonal forecasts, especially when participatory communication practices were established to overcome farmers' difficulty in understanding and applying the information. However, use of the forecast information goes only a small way toward overcoming the challenges farmers face to maintain subsistence levels of production.

Researchers have suggested that seasonal climate forecasts, based on ENSO predictions, could have significant positive benefits for food security (3, 4). Moreover, seasonal climate forecast communication is but one example of a major identified challenge for sustainable development and poverty reduction, namely the application of locally specific scientific information to help people make better livelihood choices (5). Using information to adapt to anticipated changes is an important step that communities can take to become less vulnerable to global change (6, 7).

The first major success in climate forecast application occurred in 1992, when the Brazilian state of Ceará warned farmers of an impending El Niño and supplied them with free drought-tolerant seeds, resulting in a dramatic increase in their yields over what they would have otherwise received (8). Several national and international meteorological organizations have since developed processes for ensuring that seasonal climate forecasts would be communicated to national-level decision makers (9–11). National-level policy makers in the disaster relief and water management sectors have been shown to gain value from the forecasts, as have large-scale commercial farmers (12, 13).

Crop models have demonstrated the potential economic value of the forecasts to subsistence farmers as well (2, 14), and several countries communicate the forecasts to them (15). In one such country, Zimbabwe, farmers altered crop management decisions during the 1997–1998 El Niño and the 1998–1999 La Niña, even when faced with severe resource constraints (16). The latter study analyzed farmers' reported decisions in response to predictions of drought (1997–1998) and wetter conditions (1998–1999) and concluded that the value of forecast use may be at least as high in normal to wet years as in dry years, because farmers appeared to take advantage of a good forecast to plant a greater proportion of less drought-tolerant but much higher-yielding long-season maize. The study did not, however, measure the effects of different management decisions made in response to the forecasts.

Despite these studies showing a willingness to change decisions, actual benefits of seasonal precipitation forecasts to individual resource-constrained subsistence farmers have yet to be demonstrated. Indeed, there is little evidence that the use of forecasts alone, without a concomitant distribution of seed, leads to improved harvests (12, 17). In Brazil, where drought-tolerant seed was distributed during the 1991–1992 El Niño, early success was soon followed by a forecast that many users considered to have been in error, resulting in decreased reliance on the forecast in subsequent years (18, 19). In Zimbabwe during the 1997 ENSO warm event, one of the responses to the media's exaggerated forecast was a reduction in the crop area planted, both as farmers chose to purchase less seed and as restricted credit narrowed their options; reliance on the forecast led to a decrease, rather than an increase, in yields (20), and many people criticized the forecasts (21, 22).

Empirical study has identified several roadblocks to using the forecasts. For example, farmers often still hear of the forecasts after they have made their planting decisions, and say they neither understand nor trust the information (23). An important factor limiting both the use of forecasts to make different decisions and the likelihood that those decisions will be appropriate appears to be the method by which forecasts are communicated (22). Several studies suggest the need to develop, over many years, a forecast communication system that involves the

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Abbreviations: ENSO, El Niño/Southern Oscillation; OND, October–December; JFM, January–March; RHI, relative harvest index.

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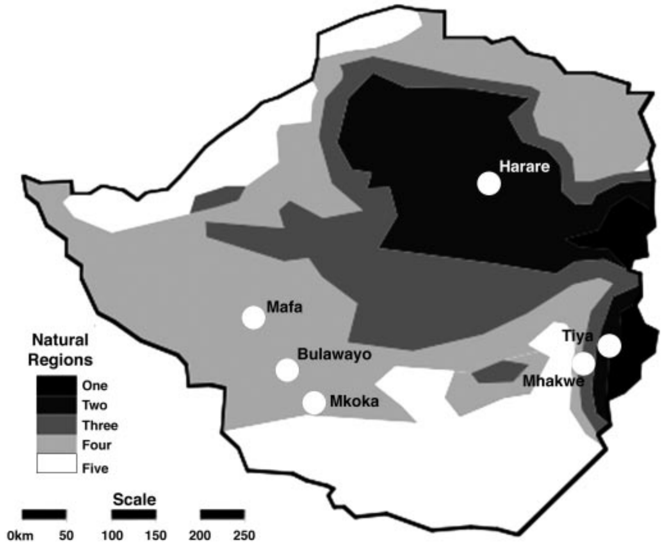

Fig. 1. Map of Zimbabwe showing approximate boundaries of natural regions, study sites, and the two largest cities, Harare and Bulawayo. The natural regions refer to labels used by the Zimbabwe Agricultural Extension Service to denote areas of homogeneous crop suitability, based on annual rainfall, duration of growing season, and temperature, with natural region one receiving the most rainfall. Most subsistence farming in Zimbabwe takes place in natural regions three and four.

active participation of the farmers themselves, and in so doing, to build the salience, credibility, and legitimacy of the forecasts (12, 24, 25).

To justify the continued flow of resources to develop and communicate forecasts to subsistence farmers, then, it would be helpful to answer two empirical questions. First, do farmers who use the information to make different decisions actually benefit from having done so? Second, are subsistence farmers who have access to a sustained participatory forecast communication process more likely to use the information than those who hear it through less interactive channels? Answering such questions has been made difficult by a set of methodological challenges associated with obtaining reliable data (26).

Methods

We carried out a pilot study in Zimbabwe to answer these two questions. We located the study in Zimbabwe because its climate is strongly influenced by El Niño (1), because the government is actively developing seasonal rainfall forecasts to be useful for subsistence farmers (15), and because these farmers face significant resource constraints typical for subSaharan Africa (27). We selected four villages as our study sites, representing a cross section of Zimbabwean growing conditions (Fig. 1). Tiya has a population of ≈1,000 and receives an average annual rainfall of ≈900 mm. Farmers here typically plant a mixture of medium- and long-season maize varieties for their staple crop. Mhakwe has a population of ≈2,500 and receives an average annual rainfall of ≈650 mm. Farmers here typically plant medium-season maize. Mafa has a population of ≈1,000 and receives an average annual rainfall of ≈550 mm. Mkoka has a population of ≈5,800 people and receives an average annual rainfall of ≈450 mm. Farmers in both Mafa and Mkoka plant a mixture of short-season maize, sorghum, and millet as their staple crops.

These communities, as with all of Zimbabwe, already have access to the seasonal rainfall forecasts developed at the annual Southern African Regional Climate Outlook Forum (SARCOF). The SARCOF forecasts are downscaled, interpreted, and disseminated by the Zimbabwe Department of Meteorological Services, with radio being the most common medium for people to learn of them. The forecasts contain rainfall estimates for the early (October–December, OND) and late (January–March, JFM) parts of the growing season, in the form of probabilities for rainfall totals falling in the ranges of below normal (a range defined by the 10 driest of the past 30 seasons), normal, or above normal (a range defined by the 10 wettest of the past 30 seasons).

Beginning in September 2000, we held a series of annual participatory climate forecast workshops in each village, designed to assist a group of ≈50 farmers in each village to better understand the forecast and to be able to apply it to their farm management decisions. In Mhakwe and Tiya, the agricultural extension service officer living in the village personally invited each workshop participant. In Mafa, the headmaster of the village primary school invited participants, whereas in Mkoka, the village chief invited participants. We asked these local coordinators to invite a random sample of farmers, based on census data, with the constraint of inviting equal numbers of men and women. In subsequent years, the local coordinator randomly invited half of the participants from the previous year's workshop and a new random sample of men and women, again based on census data, to fill out the remaining places. The workshops took place in the village primary school, lasted ≈3 hours, and were conducted in the local language, with many parts translated from English. We videotaped each workshop to obtain a transcript of farmers' questions and comments.

The workshops followed a common format, designed to assist farmers in applying the forecast information yet short enough to be a model for a more widespread communication strategy. First, we asked farmers to comment on the previous season's rainfall, and whether it agreed with their recollection of the forecast. Second, we asked farmers to comment on the success of their management practices in the past year, given the rainfall that occurred. Third, we asked farmers to offer their insights into the coming year's rainfall, based on their interpretation of local traditional rainfall indicators. Fourth, we explained to farmers the forecast for the coming season, in terms of the probabilities for below-, about-, and above-normal rainfall. Fifth, we downscaled that forecast, using farmers' own historical data for local rainfall quantities, to estimate likelihoods for ranges of actual rainfall. Sixth, we explained in simple terms and invited questions about the information used to generate the forecast, including a discussion of El Niño. Seventh, we facilitated a discussion between farmers and the local agricultural extension service officer on the appropriate farm management practices for the coming year, taking into account the forecast, the local indicators, and seed availability.

In May of 2003 and 2004 we surveyed both workshop participants and nonparticipants in each of the four communities about farming decisions, yields, and a number of demographic factors. Between 10 and 15 University of Zimbabwe students worked each year in each village as enumerators, after attending a day-long training session. Enumerators attempted to interview people who had attended the most recent workshop and a random sample of additional households in the community. Each enumerator interviewed between three and five farmers per day in the local language, with a total of between 60 and 80 surveys collected in each village in each year.

The survey elicited information on demographic variables, typical farm management practices and harvests for that farm, farming management practices and harvests for the prior year, access to forecast information, and the ways in which the forecast information had influenced their farm management practices the prior year. Yield information was broken down into area planted and harvest quantities for each crop and variety they planted: short-, medium-, and long-season maize; sorghum; and millet. Farmers also provided estimates of their historical average yields in typical good (adequate rainfall) and bad (drought) years. At the end of the survey, after farmers had provided information on yields, they answered questions related to forecast use. Farmers were informed that their individual responses would be kept confidential and would not in any way affect local decisions, including the distribution of food aid. We collected a total of 578 surveys over the 2 years. After University of Zimbabwe students had entered data into a statistical software package, we evaluated redundant and overlapping questions. We dropped variable values that contained inconsistent answers as well as outliers where estimated yields fell outside a plausible range for the particular community and variety planted.

Results

In 2002–2003, there was a mild El Niño in place, and both the OND and JFM forecasts called for 35–40-25 (35% chance of below-normal, 40% chance of normal, and 25% chance of above-normal rainfall) for the four villages. The conditions during the season, in terms of total quantities and temporal distribution, turned out to be poor. Actual OND rainfall for a region containing the two western villages was <65% of average and for a region containing the two eastern villages, 65–74% of average (28). In both regions, this fell into the below-normal category. Actual JFM rainfall for a region containing three of the villages (Mkoka, Mhakwe, and Tiya) was 75–125% of average, within the normal range, although much of this fell during a single tropical cyclone (28). Actual JFM rainfall in a region containing Mafa, which just missed the northwestern edge of the cyclone, was 65–75% of average, in the below-normal range (28). In 2003–2004, there were neutral ENSO conditions, with an OND forecast of 25–45-30 and a JFM forecast of 30–40-30 for the four villages. The conditions during the year turned out to be average to good. Actual OND rainfall for all villages was 75–125% of average, in the normal range (29). Actual JFM rainfall for the two eastern villages was 75–125% of average, whereas for the two western villages, it was 125–150% of average (29). All of these were in the normal range.

Three hundred and sixty-seven respondents had received information about what to expect for the coming rainy season, via a workshop or another medium, and of these 57% reported making different decisions because of the seasonal climate forecast. The two main ways that farmers reported using the forecast was by altering the time of planting (50% of farmers who reported making a change) or by planting different varieties of crops (40%). In 2002, many farmers planted a greater proportion of their fields with short-season varieties and planted them early, to take advantage of November rains and give themselves the opportunity to replant. In 2003, many farmers staggered their planting times and planted a greater proportion of their land. No personal demographic variables, including farmer training, education, and household assets, showed a significant relationship with reported changes made in response to the forecasts, and we omitted them from subsequent analyses.

We had identified farms in the survey instrument by first and last name of the farmer answering the survey. In the first year of the survey, unfortunately, almost all of the enumerators wrote the farmer's first initial, rather than the full first name. This led to confusion where several families shared the same last name, as was common. Based on an analysis of names, initials, and farm size, it appears that <10% of the sample could reflect households interviewed in both 2003 and 2004. However, this could mean that 2 years' data are not independent, while preventing us from treating them as panel data. In the following analyses, then, we examine not only the combined data but also each year in the aggregate. Individual years' data would be unaffected by the lack of independence between the 2 years.

Did farmers have a larger harvest than they otherwise would have had when they changed their decisions in response to the forecasts? We constructed a relative harvest index (RHI) that expresses the farmers' harvest relative to their historical baseline range:

$$RHI_i = (A_i - B_i)/(G_i - B_i),$$

where $(A_i - B_i)$ is the difference for farmer i between the actual harvest in the current year and that of a typical bad season, and $(G_i - B_i)$ is the range between typical good and bad seasons. RHI takes on a value of 0 if the farmer's actual harvest matched the estimate of a typical bad season harvest and 1 if the farmer's actual harvest matched the estimate of a typical good season harvest. RHI can also take on values outside of this range, if the actual harvest falls outside of the estimated range of bad to good years' harvest.

The RHI corrects for farmers' biases in estimating quantities, because it is a unitless metric and allows one to compare farms with very different average levels of productivity. However, it does introduce the possibility of measurement error, because it requires farmers to estimate three harvest quantities (actual, good, and bad) for each of the seed varieties they typically plant, as well as strategic behavior. We were concerned that some farmers might have strategically reported a combination of a very low actual harvest in combination with a high bad harvest estimate; they may have incorrectly believed this would portray the current year as catastrophic to secure food aid, even though we informed them that all household identifiers would remain confidential. We dropped the three outliers in this direction, where farmers reported a bad harvest to be more than two-thirds of a good harvest, indicating an overestimate of the bad harvests, with an actual harvest reported to be below this range. We also dropped all observations where bad harvest estimates met or exceeded good harvest estimates, as an additional filter for measurement error. To test for any potential bias in the RHI arising from farmers' poor estimation of their typical bad or good harvests, we examined the correlation with the reported changing of decisions (useforecast); there were no significant correlations between the useforecast and either reported bad harvests (Student's t = 0.562, P = 0.574), good harvests (Student's t = 0.997, P = 0.319), or the range between bad and good (Student's t = 1.06, P = 0.288).

Model 1 in Table 1 shows the results of an ordinary least-squares regression, with RHI as the dependent variable. In addition to a dummy variable for useforecast, we included

Table 1. Regression coefficients for value of forecast use and workshop attendance

Explanatory variable	Model 1, both years	Model 2, 2002–2003	Model 3, 2003–2004
Useforecast	0.094**	0.036	0.187*
	(0.046)	(0.039)	(0.099)
Year 2004	0.301***		
	(0.035)		
Mhakwe	−0.113*	−0.081	−0.174
	(0.051)	(0.061)	(0.117)
Tiya	0.104*	0.101*	0.087*
	(0.060)	(0.061)	(0.109)
Mafa	0.030	0.008	0.076
	(0.053)	(0.049)	(0.115)
Constant	0.044	0.071	0.330***
	(0.040)	(0.048)	(0.074)
n	495	255	240
R^2	0.157	0.042	0.068

Coefficient significance: *, 0.10; **, 0.05; and ***, 0.01 (standard errors in parentheses).

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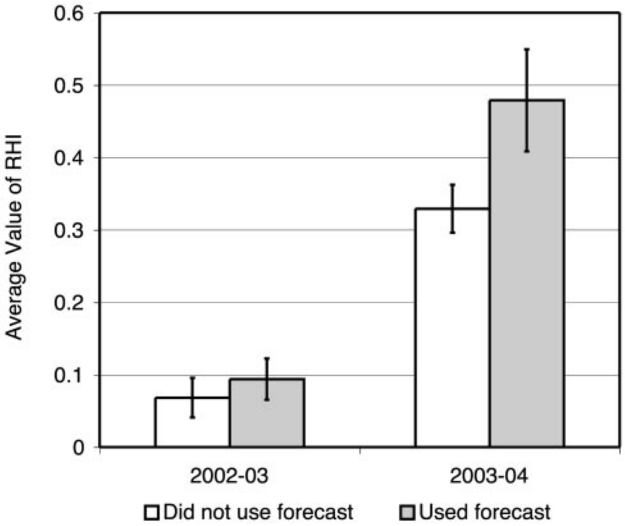

Fig. 2. Average values of the RHI within groups divided by year and reported use of forecast information. The gray bars show those who could list a specific change made on account of the forecast. Error bars reflect one standard error within each group.

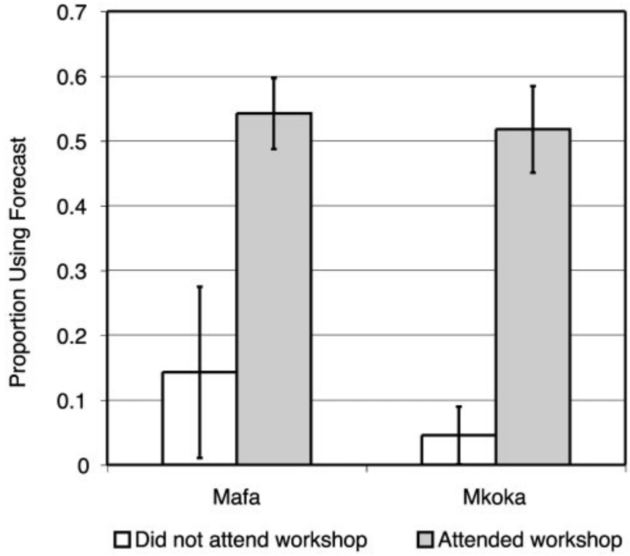

Fig. 3. Proportions reporting using forecast information within groups divided by location and workshop attendance. The white bars are limited to the subsample that reported hearing the forecast in that year through a medium other than the workshop.

dummy variables for year and location; the location variables were significant in the aggregate [F (3, 489) = 7.97, $P < 0.001$]. Because the variance in the RHI was correlated with location and year [Cook–Weisberg test for heteroskedasticity, $\chi^2(1) = 36.24$, $P < 0.001$], we generated bias-corrected robust standard errors. The coefficient for the useforecast variable is positive and significantly different from zero ($P = 0.039$), suggesting that farmers using the forecast had higher harvests relative to their historical amounts, compared with farmers not using the forecast. The coefficient for year 2004 is also significantly different from zero ($P < 0.01$), indicating that farmers did significantly better in 2003–2004 than in 2002–2003, compared with their normal range of harvests. Model 1 as a whole is a significant predictor of the RHI [F (5, 489) = 17.71, $P < 0.001$]. However, the R^2 is only 0.157, meaning that the model predicts only a small proportion of the variance in the RHI. Model 2 in Table 1 is an ordinary least-squares regression limited to the 2002–2003 year. It shows no significant effect of forecast use on relative harvest, and indeed the regression model itself is only marginally significant [F (4, 250) = 2.29, $P = 0.061$]. Model 3, for the 2003–2004 year, shows a marginally significant effect of forecast use ($P = 0.061$), and the model as a whole is significant [F (4, 235) = 4.53, $P = 0.002$]. The lower R^2 in the latter two models than in Model 1 reflects the omission of the year covariate, which is the most important predictor of harvest. Fig. 2, which shows average values of the RHI in each year according to whether farmers reported using the forecast, illustrates these results. There was a small but insignificant difference in 2002–2003 and a larger and marginally significant difference in 2003–2004.

The RHI is not normally distributed (Shapiro–Wilk W test, $z = 9.49$, $P < 0.001$). Although this does not invalidate the ordinary least-squares coefficient estimates, it does require other tests to confirm their statistical significance. The difference in means test should provide robust confidence levels, given the sample size much larger than 30. The difference was not significant in 2002–2003 (Student's $t = 0.65$, $P = 0.52$) but was significant in 2003–2004 (Student's $t = 2.18$, $P = 0.03$). The nonparametric and more conservative Mann–Whitney test for the 2003–2004 data showed marginal significance ($z = 1.70$, $P = 0.089$).

To examine the effects of the workshops, we first used the relationship between reported good harvests and workshop attendance to verify that the sample of workshop attendees was unbiased. The two communities where an agricultural extension service (AREX) officer invited workshop attendees were problematic, either because the AREX office did in fact invite a biased sample, or because a biased sample responded to the invitation. Workshop attendees reported significantly higher good harvests in Mhakwe (Student's $t = 2.77$, $P < 0.01$) and Tiya (Student's $t = 2.06$, $P = 0.04$), suggesting that the sample of workshop participants was weighted toward the more successful farmers. In Mkoka, those not attending the workshop reported good harvests 28% higher than those attending, but the effect was not significant (Student's $t = 1.02$, $P = 0.31$). In Mafa, those not attending the workshops reported good harvests 27% lower than those attending, but this effect was also not significant (Student's $t = 1.56$, $P = 0.12$). We thus analyzed just these two communities to examine the effect of workshop participation on forecast use. To gain a clearer picture of the effect of workshop attendance, we consider only those respondents who learned of the forecast, either at a workshop or through another medium.

Fig. 3 shows that in both communities, people attending the workshops were significantly more likely to report using the forecasts [Mafa $\chi^2(1) = 4.12$, $P = 0.04$; Mkoka $\chi^2(1) = 14.9$, $P < 0.001$]. Fig. 4 aggregates the two communities but examines each year separately. In 2002–2003, no farmers who had not attended a workshop made a different decision because of the workshop, whereas almost two-thirds of the farmers attending a workshop did so. The main difference appears to be that farmers who had attended the workshop learned they could respond to the forecast by planting earlier or staggering their planting; farmers not attending the workshop responded to the poor forecast by continuing to plant the most drought-tolerant crops, i.e., making no change. In 2003–2004, there was not a significant difference between those attending the workshop and those not [$\chi^2(1) = 1.17$, $P = 0.28$].

Discussion

There are several limitations of the study design. First, we do not draw a clear connection between the management decision made in response to the forecast and any resulting change in yields, showing which management decisions were most effec-

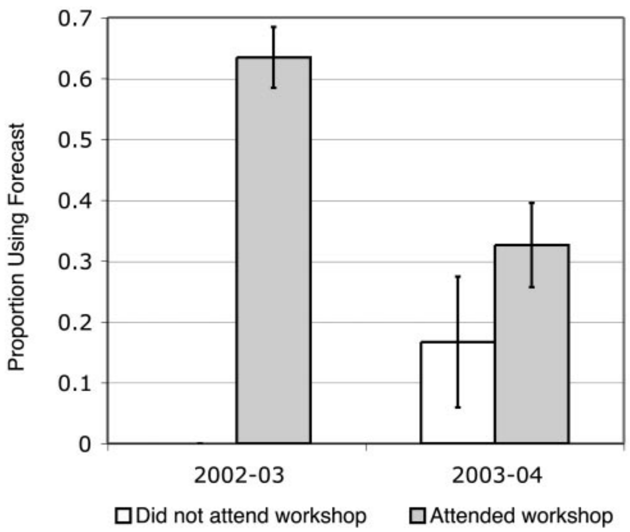

Fig. 4. Proportions reporting using forecast information within groups divided by year and workshop attendance. The sample is limited to the communities of Mafa and Mkoka. The white bars are limited to the subsample that reported hearing the forecast in that year through a medium other than the workshop.

tive. Ideally, one would want to track carefully the management decisions that farmers made and validate reported differences in yield with a crop model, incorporating all decisions in fine detail. In practice, we were not able to do this, given our choice to use a larger sample of farmers, letting them make their own decisions, with our influence limited to a short workshop. Second, our reliance on farmers' estimated harvests, both in the current year of the survey and in past years, has most likely introduced measurement error in the dependent variable, RHI. As long as it is unbiased, this error will not lead to biased estimates of the relationship between RHI and the independent variables, but it could increase the observed variance in these estimates. In the case of the regression models in Table 1, removing the measurement error could lead to greater significance of the coefficient estimates. However, measurement error could also have led us to accept the workshops as unbiased samples of farmers in Mafa and Mkoka. It should be noted that any potential bias in the sample of workshop attendees goes in the opposite directions between Mafa and Mkoka, whereas the observed effect on forecast use is the same. Combined with the lack of association between good and bad harvests and reported forecast use, this supports the finding of workshop importance even in the face of a potential biased sample within the two separate communities. To remove the measurement error, we would have needed longitudinal data, showing what survey respondents' harvests had been over many past years. Such data do not exist at the farmer level. A third limitation derives from the ambiguity of farmer identification in the survey instrument. To draw robust conclusions over multiple years' data, it would be important to identify farms and farmers by location, such as by equipping enumerators with global positioning system transceivers to mark exact coordinates. The relationship between forecast use and RHI found for the 2003–2004 year, as seen in Table 1, Model 3, and Fig. 2, is not affected by this potential problem.

Notwithstanding these limitations, the results from Mafa and Mkoka offer quantitative evidence that a more carefully designed communication strategy enhances people's willingness to change their decisions in response to information. These results are consistent with the conclusions drawn from several case studies, in which people have expressed a desire for more participatory forecast communication (12). This finding is important, because it suggests that the added expense of the more interactive communication process may be worthwhile, if policy makers want to increase farmers' use of new information. This has relevance not only for the application of climate forecasts but also for other types of technical information related to sustainable development and climate-change adaptation.

Second, these results offer quantitative evidence that use of climate forecast information alone can benefit resource-constrained developing country farmers. This is consistent with the evidence from Brazil in 1991–1992, but here it can be seen in the absence of a program to distribute, free of charge, appropriate seed varieties. The use of forecasts was associated with an increase in harvests, compared with farmers' typical range of harvests, of 9.4% across the 2 years and 18.7% in the 2003–2004 season. The significance of the second of these estimates is not affected by any problems caused by repeated sampling of the same farmers and has been validated with a nonparametric test. Although the difference is small compared with the year-to-year variability in harvests due to climate and other factors that we were not able to measure, it suggests that climate forecasts are of value to subsistence farmers.

It is an interesting feature of the data that the observed effect of the use of the forecasts was both greater in magnitude and more significant in the second year of the study. This is again consistent with prior evidence from Zimbabwe, which suggested that forecast value may be higher in non-El Niño years. Although it may be in drought years that forecasts are of the greatest value to national-level planners attempting to prepare for food insecurity, it appears that forecasts benefit farmers the most when they give them the opportunity to take advantage of good conditions. At the same time, Fig. 4 reveals that the effect of the workshops may have been greater in the first year, when drought was predicted. This is again consistent with the prior evidence, which suggested that farmers already manage risk, planting short-season varieties out of concern for likely drought. At least in dry areas, such as Mafa and Mkoka, a forecast lacking specific suggestions for change would not cause farmers to alter their behavior. A forecast workshop, however, can begin to identify smaller changes farmers can make, changes which may have very little effect on yields. By contrast, a forecast of better rains would have more obvious implications for these farmers, whether they heard the forecast over the radio or in a workshop. Such a forecast would be more valuable to farmers, whereas the added value of the workshop itself would be less.

These results represent a quantitative estimate of value to individual farmers obtained from using forecast information to make different decisions. They answer the question: Are farmers who use the forecasts better off than they otherwise would have been? Given that these farmers must survive from the crops they grow, the answer appears to be "yes." At the same time, however, the results show that climate forecasts go only so far to improve farmers' livelihoods; forecasts may be less valuable to farmers than other potential interventions, such as better access to credit to purchase inputs or install irrigation, or lower prices for fertilizer. The amount of variance explained by the forecasts in any one year is small, and the difference between a good and a bad year is far more important.

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